“PokeTrade Shopkeeper” Agent

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Abstract

The trading card market is highly dynamic, with card values fluctuating based on condition, rarity, demand, and recent sales trends across multiple online marketplaces. Buyers and sellers often rely on subjective judgment or manual price comparisons, which can result in inefficient negotiations and inconsistent pricing outcomes. This project addresses the problem of assisting buyers in determining fair market value and negotiating optimal purchase prices through an AI-driven agentic system.

We propose an autonomous AI agent that integrates real-time market data from online card marketplaces and historical sales records to estimate the true market value of collectible trading cards. The system employs data extraction and feature engineering techniques to assess card attributes such as edition, condition, grading status, and recent transaction prices. A pricing model generates a recommended fair value and target negotiation range. Building on this valuation, a negotiation agent applies rule-based and reinforcement-learning-inspired bargaining strategies to interact with sellers, dynamically adjusting offers based on seller responses, counteroffers, and market confidence levels.

Experimental results demonstrate that the AI agent consistently produces price estimates within an acceptable margin of observed market values while achieving negotiated prices below initial asking prices in a majority of simulated negotiation scenarios. Compared to baseline static pricing approaches, the agentic system improves purchase efficiency by reducing overpayment and shortening negotiation time. These results suggest that agent-based AI negotiation frameworks can effectively support real-world digital marketplaces by combining market intelligence with adaptive bargaining behavior.

Introduction

The trading card marketplace presents a challenging pricing environment due to rapidly changing market conditions, fragmented data sources, and subjective seller valuations. Buyers often struggle to determine a fair market price and must rely on time-consuming manual research or intuition when negotiating with sellers, which can lead to overpayment or failed transactions. This problem is important as the popularity and monetary value of collectible cards continue to grow, increasing the financial risk for individual buyers and small-scale traders. To address this, we developed an AI-driven agentic system that automatically evaluates real-time and historical market data to estimate accurate card values and conducts adaptive price negotiations with sellers. Our results show that the system produces market value estimates closely aligned with recent sale prices and successfully negotiates lower purchase prices compared to static or manual bargaining approaches, demonstrating the effectiveness of AI agents in supporting data-driven decision-making and negotiation within digital marketplaces.

Data

This project utilizes structured and semi-structured data collected from online trading card marketplaces to estimate market value and support automated price negotiation. The primary data consists of historical card sales records, current listing prices, and card metadata. Each record includes attributes such as card name, edition or set, year of release, card condition (e.g., raw, graded, or professionally certified), grading score when available, asking price, final sale price, and transaction date. Additional contextual data, such as seller reputation and listing duration, is also incorporated when available.

The data was sourced from publicly accessible online marketplaces and price-tracking platforms commonly used by trading card collectors. In total, the dataset contains approximately 150,000 historical sales records spanning multiple card categories and time periods, along with several thousand active listings used for real-time price evaluation.

To prepare the data for modeling, several preprocessing steps were required. Records with missing or inconsistent pricing information were filtered out, and duplicate listings were removed to prevent skewed valuations. Textual fields, such as card descriptions and condition labels, were normalized using tokenization and standardized naming conventions. Prices were adjusted for outliers and extreme values to reduce the influence of abnormal transactions. Additionally, temporal features were engineered to account for recent market trends, ensuring that the valuation model emphasized current market behavior. These preprocessing steps were essential to ensure data quality, consistency, and reliability for accurate price estimation and effective negotiation strategies.

Software

The system was implemented using a cloud-native AI architecture centered on Google's ecosystem. Gemini was used as the Large Language Model to support advanced reasoning, dialogue management, and decision-making within the agentic negotiation framework. Agent coordination, state management, and tool invocation were handled using the Google Agent Development Kit (ADK), enabling structured agent workflows and modular separation between valuation and negotiation components. The backend services were developed in Python, which facilitated data ingestion, preprocessing pipelines, feature engineering, supervised learning inference, and agent policy execution.

The application was deployed on Google Cloud Platform using Cloud Run, providing containerized, serverless execution with automatic scaling and request-based resource allocation. A web-based frontend implemented in HTML and JavaScript communicated with the backend via HTTP APIs, enabling real-time user interaction and agent responses. Development and deployment workflows were supported through Google Cloud Shell and local terminal environments, allowing for continuous testing, container builds, and cloud integration. This software stack enabled a scalable, modular, and reproducible implementation of the agentic market valuation and negotiation system.

Methodology

To address the challenge of accurately valuing trading cards and negotiating fair purchase prices, we designed an AI agentic system composed of two coordinated components: a market valuation agent and a negotiation agent. This approach directly aligns with the problem outlined in the introduction, as it combines data-driven price estimation with adaptive decision-making during buyer–seller interactions.

The valuation agent uses supervised machine learning techniques to predict fair market value based on historical sales data and current listings. Features such as card condition, grading score, edition rarity, and recent sale trends are extracted and engineered to capture key drivers of price variation. This model prioritizes recent transactions through temporal weighting, ensuring that estimates reflect current market conditions. This approach is appropriate because trading card prices are highly sensitive to time and demand fluctuations, making static or rule-based pricing insufficient.

Building on the valuation output, the negotiation agent applies an agent-based bargaining strategy that dynamically adjusts offers in response to seller behavior. The agent follows a constrained optimization framework, balancing the goal of minimizing purchase price with constraints on acceptable deal likelihood and time-to-agreement. Simple reinforcement-learning-inspired policies and heuristic rules—such as concession rates and walk-away thresholds—were used to guide negotiation decisions. This choice reflects practical constraints of real-world marketplaces, where full reinforcement learning is often infeasible due to limited interaction data.

Alternative approaches were considered, including fixed-price threshold models and fully end-to-end reinforcement learning negotiation systems. However, fixed-price methods lack adaptability, while end-to-end reinforcement learning requires extensive interaction data and introduces stability and interpretability challenges. By separating valuation and negotiation into modular agents, our method remains interpretable, data-efficient, and robust.

This methodology demonstrates the application of core skills developed during the quarter, including feature engineering, supervised learning, agent-based system design, and decision-making under uncertainty. The modular agentic framework also allows for future extensions, such as multi-agent competition or seller behavior modeling, making it a scalable and effective solution for automated marketplace negotiation.

Experiments and Results

To evaluate whether the proposed AI agentic system effectively addresses the problems of market valuation and price negotiation, we conducted a series of controlled experiments focusing on valuation accuracy, negotiation performance, and system robustness. These experiments were designed to isolate the impact of individual components and compare our approach against simpler baselines.

First, we evaluated the **market valuation agent** by comparing its predicted prices against actual historical sale prices. Performance was measured using Mean Absolute Error (MAE) and percentage error within a tolerance band (±10%). The model was compared against two baselines: (1) a simple average of recent sales prices and (2) a rule-based heuristic using condition-adjusted price averages. Results showed that the machine learning–based valuation model consistently achieved lower MAE and a higher proportion of predictions within the acceptable error range, demonstrating the benefit of feature engineering and temporal weighting.

Next, we assessed the **negotiation agent** using simulated buyer–seller interactions. Sellers were modeled with varying strategies, including fixed-price, slow-concession, and aggressive-counteroffer behaviors. We compared our adaptive negotiation agent against a static discount strategy (e.g., always offering a fixed percentage below asking price). Key metrics included final purchase price relative to market value, negotiation success rate, and number of negotiation rounds. The agentic negotiation strategy achieved lower average purchase prices while maintaining comparable or higher agreement rates, indicating improved efficiency.

To better understand system behavior, we conducted an **ablation study** by disabling key components such as temporal price weighting and dynamic concession adjustment. Removing these components led to noticeable drops in valuation accuracy and negotiation success, confirming their importance. We also experimented with different concession rates and walk-away thresholds to analyze sensitivity and trade-offs between deal likelihood and price minimization.

Finally, we examined **failure modes**, including sparse data for rare cards and sellers with unrealistic pricing expectations. Visualization of price distributions and negotiation trajectories highlighted scenarios where the agent chose to exit negotiations rather than overpay, reflecting appropriate risk-aware behavior. Overall, these experiments demonstrate that the proposed agentic approach effectively improves both pricing accuracy and negotiation outcomes compared to baseline methods.

Conclusion

This project demonstrates that an AI agentic approach can effectively support both market valuation and price negotiation in the trading card marketplace. Through experimental evaluation, we learned that data-driven valuation models significantly outperform simple averaging or rule-based pricing methods, particularly when temporal trends and card-specific features are incorporated. Accurate valuation proved to be a critical foundation for successful negotiation, as unreliable price estimates led to poorer bargaining outcomes or unnecessary negotiation failures. Additionally, the use of adaptive, agent-based negotiation strategies resulted in consistently lower purchase prices while maintaining high agreement rates, showing that intelligent concession planning is more effective than static discount approaches.

Another key insight is the importance of modular system design. Separating valuation and negotiation into distinct agents improved interpretability, robustness, and ease of experimentation. The ablation studies further confirmed that components such as temporal weighting and dynamic concession adjustment play a substantial role in overall system performance. The analysis of failure cases also highlighted that strategically walking away from overpriced listings is often preferable to forcing a deal, reinforcing the value of risk-aware decision-making in automated agents.

Several extensions and new applications can build upon this work. Future improvements could include incorporating real-time seller behavior modeling using online learning, expanding the negotiation agent with full reinforcement learning when sufficient interaction data becomes available, and integrating image-based card condition assessment using computer vision. Beyond trading cards, this agentic framework can be applied to other collectible and resale markets such as sneakers, used electronics, NFTs, or real estate micro-transactions. Overall, this work suggests that AI agentic systems have strong potential to enhance pricing transparency, negotiation efficiency, and decision-making in dynamic digital marketplaces.